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A New EDAS-based In-sample-Out-of-sample Classifier for Risk-Class Prediction

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Abstract

Purpose – Nowadays, the field of data analytics is witnessing an unprecedented interest from a variety of stakeholders. The purpose of this paper is to contribute to the subfield of predictive analytics by proposing a new non-parametric classifier.

Design/methodology/approach – The proposed new non-parametric classifier performs both in-sample and out-of-sample predictions, where in-sample predictions are devised with a new EDAS-based classifier, and out-of-sample predictions are devised with a CBR-based classifier trained on the class predictions provided by the proposed EDAS-based classifier.

Findings – The performance of the proposed new non-parametric classification framework is tested on a dataset of UK firms in predicting bankruptcy. Numerical results demonstrate an outstanding predictive performance, which is robust to the implementation decisions' choices.

Practical implications – The exceptional predictive performance of the proposed new non-parametric classifier makes it a real contender in actual applications in areas such as finance and investment, internet security, fraud, and medical diagnosis, where the accuracy of the risk-class predictions has serious consequences for the relevant stakeholders.

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Originality/value – Over and above the design elements of the new integrated in-sample-out-of-sample classification framework and its non-parametric nature, it delivers an outstanding predictive performance for a bankruptcy prediction application.

Keywords: In-sample Prediction, Out-of-sample Prediction, EDAS Classifier, CBR, k-Nearest Neighbour Classifier, Bankruptcy, Risk Class Prediction

1. Introduction

Nowadays, the use of analytical methods in extracting intelligence from data is increasingly gaining popularity amongst a variety of public and private sectors' stakeholders. The popularity of descriptive analytics techniques, predictive analytics techniques, and prescriptive analytics techniques varies substantially from one industry to another. Predictive analytics techniques however are very popular in the financial industry, amongst many others, where high accuracy in risk-class predictions is crucial for decision-making, proactive planning, and prevention of potentially high losses.

Predictive Analytics techniques for class-belonging predictions fall into two main categories; namely, parametric methods and non-parametric methods, where non-parametric prediction methods have obvious advantages over parametric ones. In this paper, we extend the toolbox of non-parametric predictive methods by proposing a new integrated classifier that performs both in-sample and out-of-sample predictions, where in-sample predictions are devised with a new EDAS-based classifier, and out-of-sample predictions are devised with a Case-based Reasoning (CBR)-based classifier trained on the class-belonging predictions provided by the proposed EDAS-based classifier – see Figure 1 for a snapshot of the design of the proposed prediction framework.

Evaluation Based on Distance from Average Solution (EDAS), first proposed by Keshavarz et al. (2015), is a multi-criteria method designed for ranking alternatives under multiple criteria. This MCDM method benchmarks all alternatives against a reference point; namely, the average performer, and makes use of the positive and negative percentage deviations from the average performer to construct an index for each alternative or entity i , say S_i , which is then used to rank alternatives. EDAS has been used to address a variety of applications; for example, building construction (Turskis and Juodagalvienė, 2016); healthy and safe built environment (Zavadskas et al., 2017); cultural heritage structures for renovation projects (Turskis et al., 2017b); conveyor selection problem (Mathew and Sahu, 2018); automated guided vehicles selection problem

(Mathew and Sahu, 2018); steel rope analysis and diagnostic (Čereška et al., 2018); public infrastructure for electric vehicles (Palevičius et al., 2018). The fuzzy version of EDAS (Ghorabae et al., 2016b) has also been used in many applications such as supplier selection (Ghorabae et al., 2016b; Keshavarz et al., 2017; Ghorabae et al., 2017b); subcontractor evaluation (Ghorabae et al., 2017a; Keshavarz et al., 2018); facility location (Ghorabae et al., 2016a); selection of solid waste disposal sites (Kahraman et al., 2017); construction equipment evaluation (Ghorabae et al., 2018); personnel selection (Turskis et al., 2017a). Although Keshavarz et al. (2015) applied EDAS to an inventory classification problem, no details on the classification rule(s) have been provided. In this paper, we propose a new in-sample classifier based on EDAS and hybridise it with CBR as an out-of-sample classifier, which is trained on the class-belonging predictions provided by EDAS.

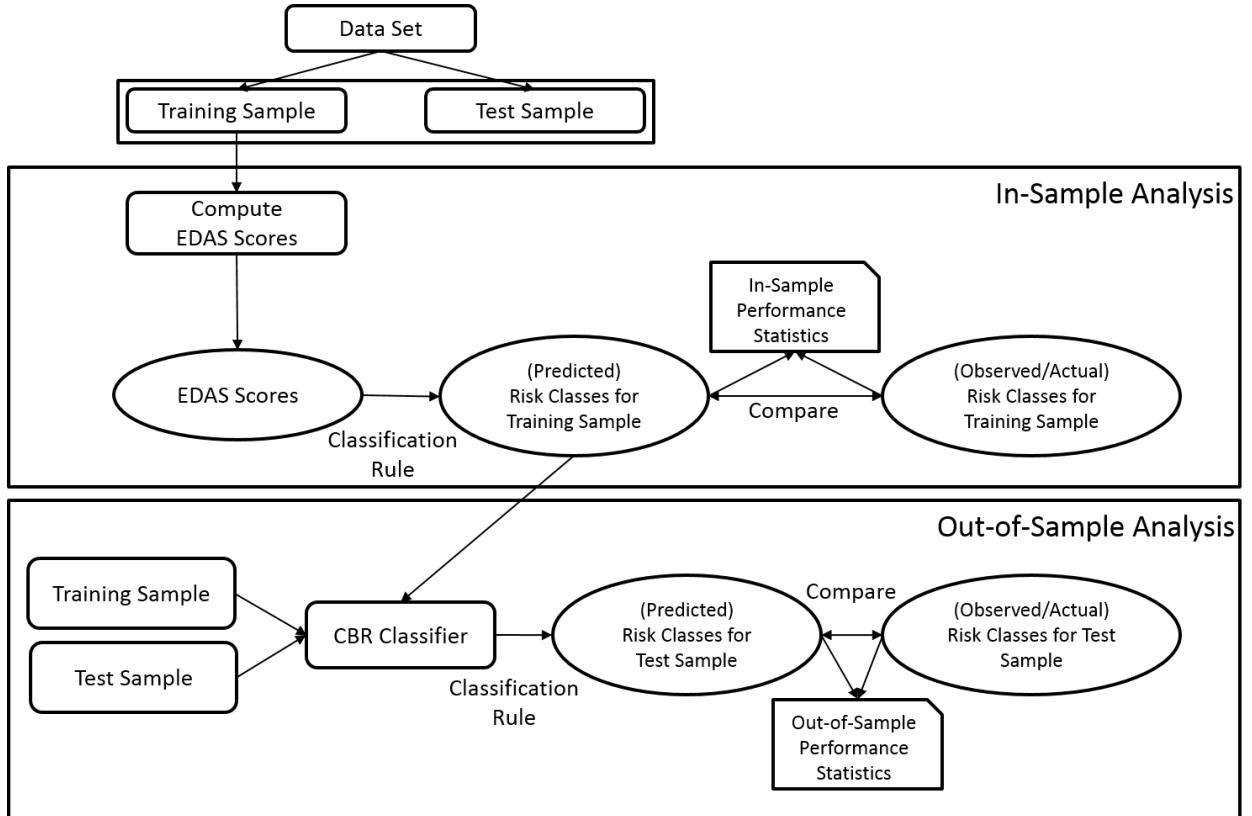


Figure 1: An Integrated EDAS-CBR Framework for In-Sample and Out-of-Sample Class-belonging Predictions

The remainder of this paper unfolds as follows. In section 2, we provide a detailed description of the proposed integrated in-sample and out-of-sample framework for EDAS-based classifiers

and discuss implementation decisions. In section 3, we empirically test the performance of the proposed framework in bankruptcy prediction of companies listed on the London Stock Exchange (LSE) and report on our findings. Finally, section 4 concludes the paper.

2. A New Integrated In-sample, Out-of-sample Classification Framework

In this section, we shall describe our integrated EDAS-based classification framework – see Figure 1 for a graphical representation of the process. Without loss of generality, we shall customize the presentation of the proposed framework to a bankruptcy application as follows:

Input: A set of n alternatives or entities (e.g., LSE listed firm-year observations) to be assessed on m pre-specified criteria (e.g., financial criteria) along with their measures (e.g., financial ratios), where the measure of each criterion could either be minimized or maximized. Thus, each entity, say i ($i = 1, \dots, n$), is represented by an m -dimensional vector of (observed) measures of the criteria under consideration, say $x_i = (x_{ij})$, where x_{ij} denote the observed measure of criterion j for entity i , and the set of x_i s shall be denoted by X . An observed risk-class membership, say Y , is also available for all entities. The historical sample X is divided into a training sample, say X^E , and a test sample, say X^T , where $\#X^E$ (resp. $\#X^T$) denote the cardinality of X^E (resp. X^T).

Phase 1: EDAS-based In-Sample Classifier

Step 1: Computation of a Reference Point or Benchmark

The reference point is a virtual benchmark representing the average performance across all alternatives i in the training sample X^E ($i = 1, \dots, \#X^E$) on each criterion j ($j = 1, \dots, m$). Such average performer or benchmark is represented by a virtual alternative described by an m -dimensional vector, say \bar{r} , where entry j corresponds to the average performance on criterion j and computed as follows:

$$\bar{r}_j = \frac{1}{\#X^E} \sum_{i=1}^{\#X^E} x_{ij}^E; j = 1, \dots, m$$

where $x_{i,j}^E$ denote the observed performance of alternative $i \in X^E$ on criterion j ($j = 1, \dots, m$).

Step 2: Computation of Individual Positive and Negative Percentage Deviations from The Reference Point or Benchmark with respect to Each Criterion

Compute the positive and negative distances with respect to each criterion j , say $d^+(i, \bar{r}, j)$ and $d^-(i, \bar{r}, j)$, between each alternative i in the training sample X^E ($i = 1, \dots, \#X^E$) and the virtual

benchmark \bar{r} , respectively, as percentage deviations from \bar{r} with respect to each criterion j so as to account for the nature of the criterion; that is, whether it is to be minimised or maximised, as follows:

$$d^+(i, \bar{r}, j) = \begin{cases} \frac{\max(0, \bar{r}_j - x_{ij}^E)}{\bar{r}_j} & \text{IF } j \in M^- \\ \frac{\max(0, x_{ij}^E - \bar{r}_j)}{\bar{r}_j} & \text{IF } j \in M^+ \end{cases} ; i = 1, \dots, \#X^E, j = 1, \dots, m$$

and

$$d^-(i, \bar{r}, j) = \begin{cases} \frac{\max(0, x_{ij}^E - \bar{r}_j)}{\bar{r}_j} & \text{IF } j \in M^- \\ \frac{\max(0, \bar{r}_j - x_{ij}^E)}{\bar{r}_j} & \text{IF } j \in M^+ \end{cases} ; i = 1, \dots, \#X^E, j = 1, \dots, m$$

where M^- (resp. M^+) denote the set of features for which lower (resp. higher) values are better.

Step 3: Computation of Overall Positive and Negative Percentage Deviations from The Reference Point or Benchmark

Choose a weighting scheme and compute overall positive and negative percentage deviations from the reference point as normalized weighted positive and negative distances, say $d^+(i, \bar{r})$ and $d^-(i, \bar{r})$, between each alternative i in the training sample $\#X^E$ ($i = 1, \dots, \#X^E$) and the virtual benchmark \bar{r} as follows:

$$d^+(i, \bar{r}) = \frac{\sum_{j=1}^m w_j \cdot d^+(i, \bar{r}, j)}{\max_i \left(\sum_{j=1}^m w_j \cdot d^+(i, \bar{r}, j) \right)} ; i = 1, \dots, \#X^E$$

and

$$d^-(i, \bar{r}) = \frac{\sum_{j=1}^m w_j \cdot d^-(i, \bar{r}, j)}{\max_i \left(\sum_{j=1}^m w_j \cdot d^-(i, \bar{r}, j) \right)} ; i = 1, \dots, \#X^E$$

where w_j is the weight of criterion j ($j = 1, \dots, m$) and weights should satisfy the following condition: $\sum_{j=1}^m w_j = 1$. Note that the weights assigned to criteria could be chosen in many ways; we refer the reader to Ouenniche et al. (2018a,b) for a sample of weighting schema used with similar MCDM methods.

Step 4: Computation of EDAS Scores

Use the overall positive and negative percentage deviations from the virtual benchmark obtained in the previous step to compute a score for each alternative i as follows:

$$S_i = \frac{1}{2}(d^+(i, \bar{r}) + 1 - d^-(i, \bar{r})) ; i = 1, \dots, \#X^E.$$

Note that S_i represent the equally weighted average of the normalized weighted positive and negative distances between alternative i and the benchmark \bar{r} . In sum, EDAS scores assign equal importance to positive and negative deviations from the average performer.

Note also that, if $d^+(i, \bar{r}, j) > 0$ for some j , then $d^-(i, \bar{r}, j) = 0$, and if $d^-(i, \bar{r}, j) > 0$ for some j , then $d^+(i, \bar{r}, j) = 0$. Therefore, for each alternative i ($i = 1, \dots, n$)

$$S_i = \begin{cases} \frac{1}{2}(1 + d^+(i, \bar{r})) & \text{IF } d^+(i, \bar{r}, j) > 0 \text{ for all } j \\ \frac{1}{2}(1 - d^-(i, \bar{r})) & \text{IF } d^-(i, \bar{r}, j) > 0 \text{ for all } j \end{cases}$$

Consequently, the higher (resp. lower) the score S_i the better (worse) alternative i is performing as compared to the benchmark.

Step 5: Computation of In-sample classification of alternatives

Use the performance scores, S_i s, computed in the previous step to classify alternatives i in the training sample X^E according to a *user-specified classification rule* into, for example, risk (e.g., bankruptcy) classes, say \hat{Y}^E . Then, compare the EDAS based classification of alternatives in X^E into risk classes; that is, the predicted risk classes, \hat{Y}^E , with the observed risk classes of alternatives in the training sample, Y^E , and compute the relevant in-sample performance statistics. The choice of a decision rule for classification depends on the nature of the classification problem; that is, a two-class problem or a multi-class problem. In this paper, we are concerned with a two-class problem; therefore, we shall provide a solution that is suitable for these problems. In fact, we propose an EDAS score-based cut-off point procedure to classify entities in X^E . The proposed procedure involves solving an optimization problem whereby the EDAS score-based optimal cut-off point, say S^* , is determined so as to optimize a given classification performance measure, say π (e.g., Type I error, Type II error, Sensitivity, Specificity), over an interval with a lower bound, say S_{LB} , equal to the smallest EDAS score of entities in X^E and an upper bound, say S_{UB} , equal to the largest EDAS score of entities in X^E . The algorithmic skeleton of the proposed procedure for determining the optimal cut-off point S^* is summarised as follows:

Initialization Step

Select an error tolerance $\varepsilon > 0$. Initialize iteration counter k to 1, set $a_k = S_{LB}$ and $b_k = S_{UB}$, and compute α_k and β_k as follows, where $\gamma = 0.618$:

$$\alpha_k = a_k + (1 - \gamma)(b_k - a_k) \text{ \& } \beta_k = a_k + \gamma(b_k - a_k);$$

Iterative Step

WHILE $(b_k - a_k) > \varepsilon$ **DO**

```
{
  IF  $\pi(\alpha_k) \leq \pi(\beta_k)$  THEN {
    Set  $a_{k+1} = \alpha_k$ ;  $b_{k+1} = \beta_k$ ;  $\beta_{k+1} = \alpha_k$ ; and  $\alpha_{k+1} = a_{k+1} + (1 - \gamma)(b_{k+1} - a_{k+1})$ ;
    Compute  $\pi(\alpha_{k+1})$ ; }
  ELSE {
    Set  $a_{k+1} = \alpha_k$ ;  $b_{k+1} = b_k$ ;  $\alpha_{k+1} = \beta_k$ ; and  $\beta_{k+1} = a_{k+1} + \gamma(b_{k+1} - a_{k+1})$ ;
    Compute  $\pi(\beta_{k+1})$ ; }
  Increment  $k$  by 1;
}
```

Estimate of the optimal cut-off score: $S^* = (a_k + b_k)/2$.

The optimal cut-off score S^* is used to classify observations in X^E into two classes; namely, bankrupt and non-bankrupt firms. To be more specific, the predicted risk classes \hat{Y}^E are determined so that firms with EDAS scores lower than S^* are assigned to a bankruptcy class and those with EDAS scores greater than or equal to S^* are assigned to a non-bankruptcy class. Note that an important feature of the design of our EDAS score-based cut-off point procedure for classification lies in the determination of a cut-off score to optimise a specific performance measure of the classifier; that is, Type I error, Type II error, Sensitivity, or Specificity, where T1 is the proportion of bankrupt firms predicted as non-bankrupt, T2 is the proportion of non-bankrupt firms predicted as bankrupt, Spe is the proportion of non-bankrupt firms predicted as non-bankrupt, and Sen is the proportion of bankrupt firms predicted as bankrupt.

Phase 2: CBR-based Out-of-sample Classifier**Step 6: Compute Out-of-sample classification of alternatives**

Use an instance of Case-based Reasoning (CBR); namely, the k-nearest neighbour (k-NN) algorithm, to classify alternatives in X^T into risk classes (i.e., bankruptcy class, non-bankruptcy class), say \hat{Y}^T . Then, compare the predicted risk classes \hat{Y}^T with the observed ones Y^T and compute the relevant out-of-sample performance statistics. A detailed description of k -NN is hereafter outlined:

Initialization Step

Choose the Case Base as X^E and the Query Set as X^T ;

Choose a *distance metric* d_{k-NN} to use for computing distances between entities;

Choose a *classification criterion*;

Iterative Step

// Compute distances between queries and cases

FOR $i_1 = 1$ to $\#X^T$ {

FOR $i_2 = 1$ to $\#X^E$ {

 Compute $d_{k-NN}(entity_{i_1}, entity_{i_2})$; }

// Sort cases in ascending order of their distances to queries and classify queries

FOR $i_1 = 1$ to $\#X^T$ {

 Sort the list $L_{i_1} = \{(i_2, d_{k-NN}(entity_{i_1}, entity_{i_2})) ; i_2 = 1, \dots, \#X^E\}$ in ascending order of distances and use the first k entries in the list $L_{i_1}(1:k, .)$ to classify $entity_{i_1}$ according to the chosen criterion; that is, the majority vote – see Table 2; in sum, $entity_{i_1}$ is assigned the predicted risk class label that the majority of its k nearest neighbors have; }

Output: In-sample and out-of-sample classifications or risk class belongings of entities, \hat{Y}^E and \hat{Y}^T , along with the corresponding performance statistics.

Finally, note that the EDAS classifier outcome depends on the average values of the measures of the criteria under consideration, \bar{r} , whose calculation depends on the given set of alternatives X^E . Therefore, inclusion or exclusion of one or several alternative; e.g., X^T , would affect the EDAS outcome unless \bar{r} is chosen or fixed at the outset by the decision maker independently from X^E . This is the main reason for choosing a CBR framework for the out-of-sample classification instead of EDAS.

In the next section, we shall report on our empirical evaluation of the proposed EDAS-CBR integrated prediction framework.

3. Empirical Results

In order to assess the performance of the proposed framework, we considered a sample of 6605 firm-year observations consisting of non-bankrupt and bankrupt UK firms listed on the London Stock Exchange (LSE) during 2010-2014 excluding financial firms and utilities as well as those firms with less than 5 months lag between the reporting date and the fiscal year. The source of our sample is DataStream. The list of bankrupt firms is however compiled from London Share Price Database (LSPD) – codes 16 (Receivership), 20 (in Administration) and 21 (Cancelled and Assumed valueless). Information on our dataset composition is summarised in Table 1. As to the

selection of the training sample and the test sample, we have chosen the size of the training sample to be twice the size of the test sample. The selection of observations was done with random sampling without replacement to ensure that both the training sample and the test sample have the same proportions of bankrupt and non-bankrupt firms. A total of thirty pairs of training sample-test sample were generated.

Observations (2010-2014)	Nb.	%
Bankrupt Firm-Year Observations	407	6.16%
Non-Bankrupt Firm-Year Observations	6198	93.84%
Total Firm-Year Observations	6605	100%

Table 1: Dataset Composition

In our experiment, we reworked a standard and well known parametric model within the proposed EDAS-CBR framework; namely, the multivariate discriminant analysis (MDA) model of Taffler (1984), to provide some empirical evidence on the merit of the proposed framework. Recall that Taffler’s model makes use of four explanatory variables or bankruptcy drivers which belong to the same category; namely, liquidity. These drivers are current liabilities to total assets, No-credit interval – as measured by the number of days the company can continue to trade if it can no longer generate revenues, profit before tax to current liabilities, and current assets to total liabilities. Note that lower values are better than higher ones for Current Liabilities to Total Assets, whereas higher values of No-credit interval, Current Assets to Total Liabilities and Profit Before Tax to Current Liabilities are better than lower ones. We report on the performance of the proposed framework using four commonly used metrics; namely, Type I error (T1), Type II error (T2), Sensitivity (Sen) and Specificity (Spe).

Since both the EDAS classifier and the k-NN classifier, trained on the in-sample classification obtained with EDAS, require a number of decisions to be made for their implementation, we considered several combinations of decisions to find out about the extent to which the performance of the proposed framework is sensitive or robust to these decisions. Recall that, for the EDAS classifier, the analyst must choose (1) a weighting scheme, and (2) the classification rule. On the other hand, for the k-NN classifier, the analyst must choose (1) the metric to use for computing distances between entities, d_{k-NN} , (2) the classification criterion, and (3) the size k of the neighbourhood. Our choices for these decisions are summarised in Table 2.

EDAS	
Decision	Options Considered and Justification, if relevant
Weighting Scheme	Equal weights w_j s
Classification Rule	VIKOR score-based cut-off point procedure, where the choice of the cut-off point optimises a specific performance measure (i.e., T1, T2, Sen, Spe)
k-NN	
Decision	Options Considered and Justification, if relevant
Metric d_{k-NN}	Euclidean, Cityblock, Mahalanobis.
Classification Criterion	Majority vote. Several criteria could have been used such as a Weighted Vote, but once again our choice is made so as to avoid any personal (subjective) preferences.
Size of the neighbourhood k	$k = 3; 5; 7$. The results reported are for $k = 3$ since higher values delivered very close performances but required more computations.

Table 2: Implementation Decisions for EDAS and k-NN

Hereafter, we shall provide a summary of our empirical results and findings. Table 3 provides a summary of In-sample statistics on the performance of the MDA model of Taffler (1984) reworked within the EDAS-CBR framework, which is an integrated in-sample-out-of-sample framework for EDAS-based classifiers. These results show that the In-sample performance of the classifier is outstanding. In fact, none of the non-bankrupt and bankrupt firms is misclassified.

On the other hand, the out-of-sample performance of the classifier is also outstanding – see Table 3. In fact, all non-bankrupt firms are properly classified. As to bankrupt firms, on average, 99.60% to 99.99% are properly classified as shown by Sensitivity, depending on the choice of the distance metric to use within CBR, where the Mahalanobis distance seems to be the less desirable choice – although the difference in performance is marginal to recommend that the Mahalanobis distance should be avoided in implementing CBR.

To conclude, our results suggest that the predictive performance of the proposed classification framework is by far superior to the predictive performance of multivariate discriminant analysis – see Table 4.

	Statistics	In-sample Performance in Percentage (%)			
		T1	T2	Sen.	Spe.
Distance Metric	Min	0	0	100	100
	Max	0	0	100	100
	Average	0	0	100	100
	Std. Dev.	0	0	0	0
	Out-of-sample Performance in Percentage (%)				
	Statistics	T1	T2	Sen.	Spe.
	Min	0	0	99.26	100
	Max	0.74	0	100	100
	Average	0.10	0	99.99	100
	Std. Dev.	0.25	0	0.25	0
Euclidean	Min	0	0	99.26	100
	Max	0.74	0	100	100
	Average	0.10	0	99.99	100
	Std. Dev.	0.25	0	0.25	0
Cityblock	Min	0	0	99.26	100
	Max	0.74	0	100	100
	Average	0.10	0	99.99	100
	Std. Dev.	0.25	0	0.25	0
Mahalanobis	Min	0	0	97.79	100
	Max	2.21	0	100	100
	Average	0.34	0	99.66	100
	Std. Dev.	0.60	0	0.60	0

Table 3: Summary Statistics of the Performance of the Proposed Framework

Statistics	In-sample Performance in Percentage (%)			
	T1	T2	Sen.	Spe.
Min	97.05	0.19	0	99.37
Max	100	0.63	2.95	99.81
Average	98.82	0.26	1.18	99.74
Std. Dev.	0.67	0.09	0.67	0.09
Statistics	Out-of-sample Performance in Percentage (%)			
	T1	T2	Sen.	Spe.
Min	0	0	0	0.15
Max	100	99.85	100	100
Average	82.20	17.01	17.80	82.99
Std. Dev.	37.43	37.66	37.43	37.66

Table 4: Summary Statistics of The Performance of MDA

4. Conclusions

The analytics toolbox of risk management is crucial for the financial industry amongst others. In this paper, we extended such toolbox with a new non-parametric classifier for predicting risk class belonging. The proposed classification framework performs both in-sample and out-of-sample predictions. From a design perspective, in-sample predictions of risk class belonging are

performed using a new EDAS-based classifier, whereas out-of-sample predictions are performed with a case-based reasoning algorithm; that is, k-nearest neighbour, which is trained on the in-sample predictions obtained with the proposed EDAS-based classifier. The proposed classification framework has many important features that drive its outstanding performance such as the design of our EDAS score-based cut-off point procedure for in-sample classification, and the choice of a k-Nearest Neighbour as an out-of-sample classifier, which is trained on the in-sample classification provided by the new EDAS-based classifier. In addition, the basic concepts behind both EDAS and CBR are easy to explain to managers.

We assessed the performance of the proposed EDAS-CBR framework using a UK dataset of bankrupt and non-bankrupt firms. Our results support its outstanding predictive performance. In addition, the outcome of the proposed framework is robust to a variety of implementation decisions. Last, but not least, the proposed classification framework delivers a very high performance similar to the DEA-based classifier proposed by Ouenniche and Tone (2017) and the MCDM classifiers proposed by Ouenniche et al. (2018a,b). There are similarities and differences between the classifier proposed in this paper and the MCDM classifiers proposed in Ouenniche et al. (2018a,b). Conceptually all these classifiers model deviations from the reference point(s). The difference between them however lies in how alternatives are rewarded or penalised for being close to or far from such reference point(s). The potential advantages of one scheme over another depend, on one hand, on the application area from a modelling perspective and, on the other hand, on the data as the performance of all these classifiers is data driven.

References

- Čereška, A., Zavadskas, E., Bucinskas, V., Podvezko, V., and Sutinys, E. (2018), “Analysis of steel wire rope diagnostic data applying multi-criteria methods”, *Applied Sciences*, Vol. 8 No. 2, pp. 260.
- Ghorabae, M., Amiri, M., Zavadskas, E., and Antucheviciene, J. (2018), “A new hybrid fuzzy MCDM approach for evaluation of construction equipment with sustainability considerations”, *Archives of Civil and Mechanical Engineering*, Vol. 18 No. 1, pp. 32-49.
- Ghorabae, M., Amiri, M., Zavadskas, E., and Turskis, Z. (2017a), “Multi-criteria group decision-making using an extended EDAS method with interval type-2 fuzzy sets”, *E+M. Ekonomie a Management*, Vol. 1, pp. 48-68.
- Ghorabae, M., Amiri, M., Zavadskas, E., Turskis, Z., and Antucheviciene, J. (2017b), “A new multi-criteria model based on interval type-2 fuzzy sets and EDAS method for supplier evaluation

and order allocation with environmental considerations”, *Computers & Industrial Engineering*, Vol. 112, pp. 156-174.

Ghorabae, M., Zavadskas, E., Amiri, M., and Antucheviciene, J. (2016a), “Evaluation by an area-based method of ranking interval type-2 fuzzy sets (EAMRIT-2F) for multi-criteria group decision-making”, *Transformation in Business & Economics*, Vol. 15 No. 3, pp. 76-95.

Ghorabae, M., Zavadskas, E., Amiri, M., and Turskis, Z. (2016b), “Extended EDAS method for fuzzy multi-criteria decision-making: an application to supplier selection”, *International Journal of Computers Communications & Control*, Vol. 11 No. 3, pp. 358-371.

Kahraman, C., Keshavarz, M., Zavadskas, E., Cevik, S., Yazdani, M., and Oztaysi, B. (2017), “Intuitionistic fuzzy EDAS method: an application to solid waste disposal site selection”, *Journal of Environmental Engineering and Landscape Management*, Vol. 25 No. 1, pp. 1-12.

Keshavarz, M., Amiri, M., Olfat, L., and Khatami, S. (2017), “Designing a multi-product multi-period supply chain network with reverse logistics and multiple objectives under uncertainty”, *Technological and Economic Development of Economy*, Vol. 23 No. 3, pp. 520-548.

Keshavarz, M., Edmundas, Z., Laya, O., and Zenonas, T. (2015), "Multi-criteria inventory classification using a new method of evaluation based on distance from average solution (EDAS)", *Informatica*, Vol. 26, No. 3, pp. 435-451.

Keshavarz, M., Amiri, M., Zavadskas, E., Turskis, Z., and Antucheviciene, J. (2018), “A Dynamic fuzzy approach based on the EDAS method for multi-criteria subcontractor evaluation”, *Information*, Vol. 9 No. 3, pp. 68.

Mathew, M., and Sahu, S. (2018), "Comparison of new multi-criteria decision making methods for material handling equipment selection", *Management Science Letters*, Vol.8 No. 3, pp.139-150.

Ouenniche, J. and Tone, K. (2017), “An out-of-sample evaluation framework for DEA with application in bankruptcy prediction”, *Annals of Operations Research*, Vol. 254 No. 1-2, pp. 235-250.

Ouenniche, J., Bouslah, K., Cabello, J. and Ruiz, F. (2018b), “A new classifier based on the reference point method with application in bankruptcy prediction”, *Journal of the Operational Research Society*, pp. 1-8. <https://doi.org/10.1057/s41274-017-0254-z>

Ouenniche, J., Pérez-Gladish, B. and Bouslah, K. (2018a), “An out-of-sample framework for TOPSIS-based classifiers with application in bankruptcy prediction”, *Technological Forecasting and Social Change*, Vol. 131, pp. 111-116. <https://doi.org/10.1016/j.techfore.2017.05.034>

Palevičius, V., Podviezko, A., Sivilevičius, H., and Prentkovskis, O. (2018), “Decision-aiding evaluation of public infrastructure for electric vehicles in cities and resorts of Lithuania”, *Sustainability*, Vol. 10 No. 4, pp. 904.

Taffler, R. (1984), “Empirical models for the monitoring of UK corporations”, *Journal of Banking and Finance*, Vol. 8 No. 2, pp. 199–227.

Turskis, Z., and Juodagalvienė, B. (2016), “A novel hybrid multi-criteria decision-making model to assess a stairs shape for dwelling houses”, *Journal of Civil Engineering and Management*, Vol. 22 No.8, pp. 1078-1087.

Turskis, Z., Ker, V., and Vinogradova, I. (2017a), “A new fuzzy hybrid multi-criteria decision-making approach to solve personnel assessment problems. Case study: director selection for estates and economy office”, *Economic Computation & Economic Cybernetics Studies & Research*, Vol. 51 No. 3, pp. 211-229

Turskis, Z., Morkunaite, Z., and Kutut, V. (2017b), “A hybrid multiple criteria evaluation method of ranking of cultural heritage structures for renovation projects”, *International Journal of Strategic Property Management*, Vol. 21 No. 3, pp. 318-329.

Zavadskas, E., Cavallaro, F., Podvezko, V., Ubarte, I., and Kaklauskas, A. (2017), “MCDM assessment of a healthy and safe built environment according to sustainable development principles: A practical neighborhood approach in Vilnius”, *Sustainability*, Vol. 9 No. 5, pp. 702.